

Research article

Modeling and estimating aboveground biomass of *Dacrydium pierrei* in China using machine learning with climate changeChunyan Wu^{a,b}, Yongfu Chen^{a,*}, Changhui Peng^{b,c,**}, Zhaochen Li^d, Xiaojiang Hong^e^a Research Institute of Forest Resource Information Techniques, Chinese Academy of Forestry, Beijing, 100091, China^b Department of Biological Science, Institute of Environment Sciences, University of Quebec at Montreal, Montreal, QC, Canada^c Center for Ecological Forecasting and Global Change, College of Forestry, Northwest A & F University, Yangling, Shaanxi, China^d Asia-Pacific Network for Sustainable Forest Management and Rehabilitation, Beijing, China^e Hainan Bawangling National Natural Reserve, Changjiang, 572722, Hainan, China

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ABSTRACT

Accurate estimations of the aboveground biomass (AGB) of rare and endangered species are particularly important for protecting forest ecosystems and endangered species and for providing useful information to analyze the influence of past and future climate change on forest AGB. We investigated the feasibility of using three developed and two widely used models, including a generalized regression neural network (GRNN), a group method of data handling (GMDH), an adaptive neuro-fuzzy inference system (ANFIS), an artificial neural network (ANN) and a support vector machine (SVM), to estimate the AGB of *Dacrydium pierrei* (*D. pierrei*) in natural forests of China. The results showed that these models could explain the changes in the AGB of the *D. pierrei* using a limited amount of meteorological data. The GRNN and ANN models are superior to the other models for estimating the AGB of *D. pierrei*. The GMDH model consistently produced comparatively poor estimates of the AGB. Three climate scenarios, including the representative concentration pathway (RCP) 2.6, RCP 4.5, and RCP 8.5, were compared with the climate situation of 2013–2017. Under these scenarios, the AGB of *D. pierrei* females with the same diameter at breast height (DBH) would increase by $13.0 \pm 31.4\%$ (mean $\pm$ standard deviation), $16.6 \pm 30.7\%$, and $18.5 \pm 30.9\%$ during 2041–2060 and $15.6 \pm 32.1\%$, $21.2 \pm 33.2\%$, and $24.8 \pm 32.7\%$ during 2061–2080; the AGB of males would increase by $16.3 \pm 32.3\%$, $21.7 \pm 32.5\%$, and $22.9 \pm 32.6\%$ during 2041–2060 and $22.3 \pm 30.8\%$, $27.2 \pm 31.8\%$, and $30.1 \pm 34.4\%$ during 2061–2080. The R^2 values of all models range from 0.82 to 0.95. In conclusion, this study suggests that these advanced models are recommended to estimate the AGB of forests, and the AGB of forests would increase in 2041–2080 under future climate scenarios.

1. Introduction

Global climate change influences the distribution (Wang et al., 2017) and structure of forests (Peñuelas et al., 2016), the stability and balance of ecosystems (Hautier et al., 2015; Kilpeläinen et al., 2017), ecosystem restoration (Deng et al., 2017a, 2017b), the functional composition of trees, and biological accumulation in forests through changes in biodiversity (van der Sande et al., 2017). The tree mortality induced by global drought and warming reveals the damage to forests caused by climate change (Kennedy et al., 2018). Forest biomass was identified as an important variable by the global climate observing system (GCOS) (Fu et al., 2017) to improve our knowledge of the forest ecosystems (Le Toan et al., 2011). Information about the impact of

climate on forest biomass can provide valuable insights to promote the natural regeneration of forests, respond to sustainability, and adapt to climate change (Kennedy et al., 2018). Therefore, understanding how climate change affects forest biomass has become particularly important.

Previous studies have reported that process-based models have been used to simulate the effects of climate change on forest biomass (Yousefpour et al., 2018). These studies found that although climate change significantly contributes to an increase in forest aboveground biomass (AGB) (Duveneck et al., 2017), deforestation and forest conversion may lead to a rapid decline in forest AGB (Peñuelas et al., 2016; Wu et al., 2017). Increased atmospheric carbon dioxide levels and higher temperatures are expected to have a positive impact on forest

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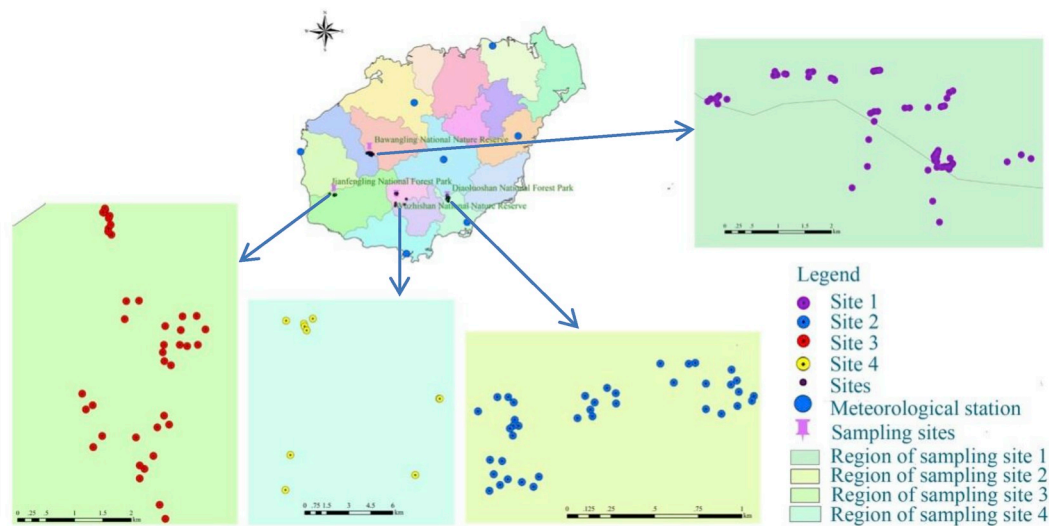


Fig. 1. Location of the study area consisting of the Bawangling National Nature Reserve, the Jianfengling National Forest Park, the Diaoluoshan National Forest Park and the Wuzhishan National Nature Reserve in China and spatial distribution of sample plots.

growth and wood production in temperate areas, and in Mediterranean and mountainous regions in the north (Lindner et al., 2010). The total tree growth/biomass will increase with the increase in temperature within a certain range (de Vries et al., 2017; Kurz et al., 2008) and exhibit a nonlinear decrease under high temperature and drought conditions (Huntingford et al., 2008). Previous studies have also derived methods to estimate forest biomass using statistical biomass models and dynamic litter and soil models from existing forest inventory data (Kilpeläinen et al., 2017). However, all of these studies focus on different climate regions in specific areas, and traditional modeling methods are commonly used (Aherne et al., 2012; Stegen et al., 2011). The nonlinear problems in dynamically changing systems are not well resolved. In addition, exploratory models have theoretical and practical significance for addressing the significant challenges of complexity in ecological data (Papadimitriou, 2002). To solve the above problem, machine learning (ML) models have become increasingly popular in forest management and protection in recent years (Chang et al., 2017; MacMichael and Si, 2018; Shafizadeh-Moghadam et al., 2018). One of the most important challenges to consider during the model prediction process is the specific nonlinear problem in a dynamically changing system (Soares and Araújo, 2016). The most advanced data processing technologies have included the group method of data handling (GMDH), generalized regression neural networks (GRNN), and adaptive neuro-fuzzy inference systems (ANFIS) with the rapid development of ML (Dou and Yang, 2018). These methods have been used to identify shell-free rice fungal populations (Chang et al., 2017; Foody and Cutler, 2006), predict and map soil organic carbon stocks in landscapes (Were et al., 2015), and accurately predict biomass heating values (Akkaya, 2016).

Significant achievements have been made through the establishment of many advanced algorithmic models. However, these prevalent algorithms are suitable for only certain plants or communities. The theories used to derive the overall plans for the environmental management of particular species or areas have complex algorithmic problems (Papadimitriou, 2012b) that can be solved by artificial intelligence methods, such as the artificial neural network (ANN) and fuzzy logic methods (Papadimitriou, 2012a; Shaker and Ehlinger, 2014). In addition, AGB estimation studies using ML are limited, especially for rare and endangered species (MacMichael and Si, 2018; Shafizadeh-Moghadam et al., 2018). Therefore, exploring the models that can be used to quickly and efficiently estimate and predict accurate biomass is particularly important. However, the application of advanced methods and technologies for plant protection and

regeneration, as well as the achievement of higher prediction accuracy, is an arduous task and a considerable exploratory research endeavor.

Rare and endangered tree species are experiencing survival difficulties due to bad living environments caused by global climate change (Dyderski et al., 2018; Fernandino et al., 2018). *D. pierrei* belongs to the *Dacrydium* genus of the Podocarpaceae family, and it appears to have become extinct in Australia during the Miocene (Norton et al., 1988). *D. pierrei* is the only species of this genus that exists in China (Li et al., 2015). Currently, this species is found in only four original tropical rainforests in Hainan Province (Chen et al., 2014; Huang et al., 2014). In addition, *D. pierrei* is classified as a third-class endangered plant under the China Red Data Book (Gunnar et al., 2011; Su et al., 2010), and as an endangered tree species. Therefore, attempting to evaluate the AGB of *D. pierrei* in China using ML models is necessary to promote protection measures for rare and endangered tree species and improve the forest regeneration ability. This method represents an innovation in this research field and a challenge of the application of ML models for AGB evaluation methods and tree species research.

In this study, five different machine learning data processing techniques (ANN, SVM, GRNN, ANFIS, and GMDH) were used to estimate the AGB of *D. pierrei* using the five-year survey data from a natural forest. The specific objectives were to (1) investigate the feasibility and capability of a variety of data processing models to simulate the AGB; (2) explore the best AGB model and predict the AGB using the developed models based on different climate scenarios; and (3) provide advice and a reference for the implementation of artificial management plans for rare and endangered tree species.

2. Materials and methods

2.1. Site description

The global distribution range of *D. pierrei* is decreasing (Farjon and Filer, 2013; Norton et al., 1988) (Fig. S1). As part of our ongoing research effort, the Bawangling National Nature Reserve (109°03'~109°17'E, 18°57'~19°11'N), the Jianfengling National Forest Park (108°39'~109°24'E, 18°24'~18°58'N), the Diaoluoshan National Forest Park (109°43'~110°03'E, 18°43'~18°58'N), and the Wuzhishan National Nature Reserve (109°32'~109°43'E, 18°48'~18°59'N), which are the only areas in China where *D. pierrei* grows, were chosen as the study sites (Chen et al., 2014) (Fig. 1). The climates in these four areas are tropical monsoon and tropical sea monsoon. The average annual temperatures are approximately 23.6 °C, 19.7 °C, 24.4 °C and 23.9 °C.

Table 1
The ranks of the diameter at breast height (DBH) of *Dacrydium pierrei*.

Rank	I	II	III	IV	V	VI	VII	VIII
DBH(cm)	≤ 10	10 < ₂ ≤ 20	20 < ₃ ≤ 30	30 < ₄ ≤ 40	40 < ₅ ≤ 50	50 < ₆ ≤ 60	60 < ₇ ≤ 70	70 < ₈ ≤ 80
Rank	IX	X	XI	XII	XIII	XIV	XV	XVI
DBH(cm)	80 < ₉ ≤ 90	90 < ₁₀ ≤ 100	100 < ₁₁ ≤ 110	110 < ₁₂ ≤ 120	120 < ₁₃ ≤ 130	130 < ₁₄ ≤ 140	140 < ₁₅ ≤ 150	150 < ₁₆

The average annual precipitation is approximately 1657 mm, 1634 mm, 2400 mm and 1690 mm. The average annual relative humidity is above 88% in all four locations. The forest coverage is greater than 98% in all four locations (Chen et al., 2014). *D. pierrei* is a dioecious plant. To avoid different AGB measurements resulting from differences in biological traits between males and females, the trees were divided into males and females during modeling. A total of 300 tree samples (from all four sites) were selected.

2.2. Data presentation

2.2.1. Biomass data

In this study, the diameter at breast height (DBH), height (H) and crown width of trees were investigated. Sample trees were divided evenly into 16 ranks according to DBH (Table 1). One standard tree was selected from each plot for biomass determination. We cut down the tree and measured the fresh weights of the stems, branches, leaves and fruits to determine the water content in the field. The samples were brought to the laboratory and oven-dried at 75 °C to a constant weight. The biomass of stems, branches, leaves and fruits was calculated using the dry weight to fresh weight ratio, and the AGB of the tree was obtained by summing all biomass values (Fu et al., 2017).

The sample trees were classified as evenly as possible into as many as three to five height classes in each DBH class. Information about the percentages of males and females, the tree height and crown width in each DBH class was obtained by data preprocessing (Fig. 2). The integral biomass dataset was randomly divided into three groups: training, validation and testing datasets. After several calculations, we found that 210 (70% of 300 samples) trees for model training, 45 (15%) trees for model validation, and 45 (15%) trees for model testing produced the best results. The characteristics of the data and related positions of the training, validation and testing datasets are summarized in Table 2.

2.2.2. Climate data

The climate data originated from the China Meteorological Data Network of the China Meteorological Administration Meteorological Data Center <http://data.cma.cn/en>. The spatial distributions of climate variables (interpolation calculation) were obtained by using ArcGIS software with geostatistical methods (Teng et al., 2017). The distribution of weather stations in Hainan Province is shown in Fig. 1. Hainan Island has a tropical maritime monsoon climate. Five bioclimatic variables were chosen: monthly average minimum temperature, monthly average maximum temperature, monthly average temperature, monthly average relative humidity, and monthly precipitation (Petus et al., 2018; Sáez et al., 2018). The observations of these variables were averaged over the period from 2013 to 2017, as shown in Fig. S2.

2.3. Model development and applications

2.3.1. Artificial neural networks (ANN)

An ANN is a large-scale adaptive power system that has a similar function and structure as the human nervous system and consists of a large number of processing units. ANN methods are widely considered important monitoring techniques to solve problems such as regression, classification and pattern recognition (Vahedi, 2016). In this study, ANN-type multilayer perception (MLP) and various architectures were used to estimate AGB (Ali et al., 2015). This type of neural network is formed by a network consisting of the main tree variables (DBH, H and crown width), one input, four hidden layers and one output layer node. The learning relationship between the input and output nodes is triggered by the hidden layer. Here, the input value is: $\sum w_i x_i$,

The output value is:

$$y = f(\sum w_i x_i - \theta) \quad (1)$$

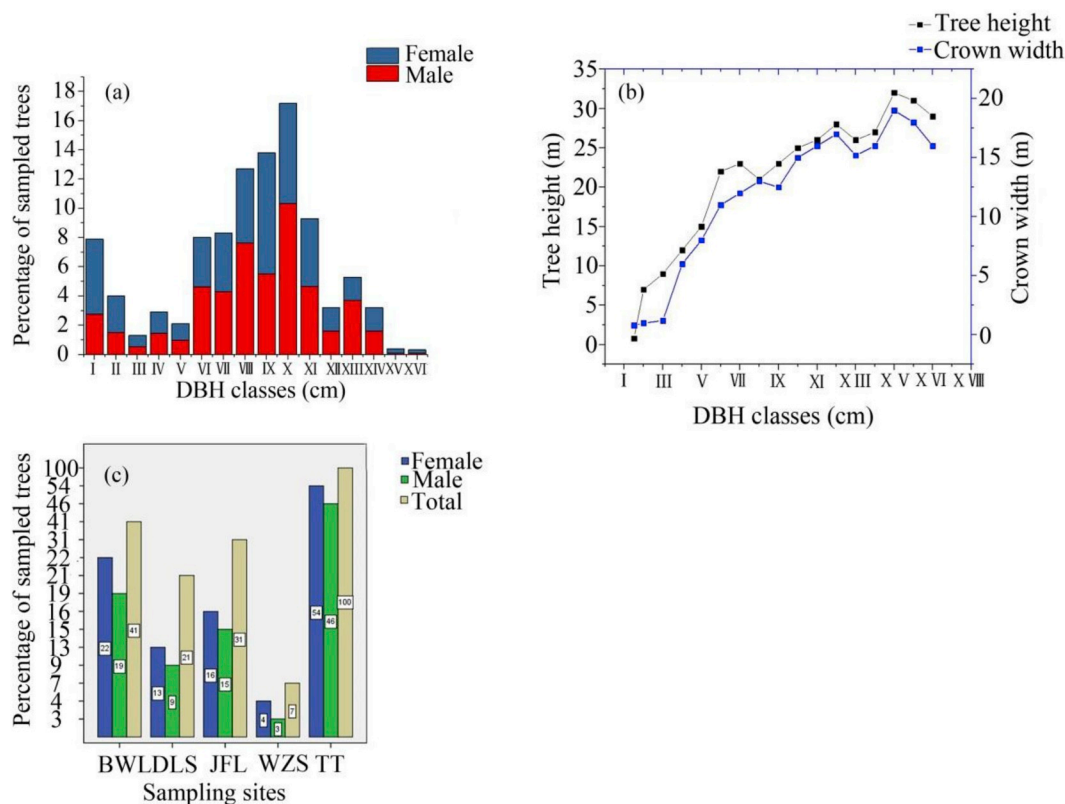


Fig. 2. The percentages and tree factor information of sampled trees. (a) Male to female ratio, diameter at breast height (DBH, cm) classes of female and male tree (female and male are sexes difference of *Dacrydium pierrei*, which is dioecious); (b) the tree height (y axis in left side) and crown width (y axis in right side) of sample trees in distribution sites; (c) the percentages of sampled trees (divided into female and male and total) in the Bawangling, the Diaoluoshan, the Jianfengling, the Wuzhishan sites and the entire distribution sites (denoted by BWL, DLS, JFL, WZS and TT, respectively).

in which, the weight (w) controls the propagation value (x) and the output value (y) from each node and was modified using the value from the preceding layer according to Equation (1); x represents the climate variables (average minimum temperature, average maximum temperature, average temperature, average relative humidity, precipitation); y is AGB; and θ is a threshold.

Table 2

Summary statistics of diameter at breast height (DBH, cm), tree height (H, m) and total aboveground biomass (AGB, kg) of *Dacrydium pierrei* by females and males for model training, validation and testing datasets used in this study (N denotes the total number of observations; Mean, Min and Max denotes average value, minimum and maximum of variables, respectively; SD denotes the standard deviation; Ku denotes kurtosis; Sk denotes the skewness of each variable. Female and Male are sex difference of *D. pierrei*, which is dioecious.

Period		Variable	N	Mean	SD	Min	Max	Ku	Sk
Training	Female	DBH	70	74.74	48.79	8.31	154.62	0.326	0.147
		H	70	21.53	23.38	0.84	30.24	0.364	0.125
		AGB	70	2225.02	2242.78	0.23	6715.67	0.385	0.194
	Male	DBH	55	68.52	49.88	10.81	150.18	0.301	0.154
		H	55	19.89	23.67	1.12	32.03	0.883	0.595
		AGB	55	2102.73	2119.62	0.22	6346.53	0.952	0.628
Validation	Female	DBH	35	79.28	54.26	8.26	169.27	0.692	0.417
		H	35	25.75	29.68	0.87	28.53	0.734	0.542
		AGB	30	2664.47	2644.91	0.25	6345.01	0.549	0.213
	Male	DBH	30	57.26	57.83	15.12	144.66	0.524	0.267
		H	30	23.80	27.88	2.58	33.92	0.365	0.165
		AGB	30	2514.28	2262.16	0.52	6727.24	0.426	0.236
Testing	Female	DBH	30	74.32	47.73	8.22	165.21	0.503	0.305
		H	30	24.27	22.56	0.61	27.49	0.544	0.269
		AGB	30	2351.91	2345.60	0.63	4994.27	0.485	0.236
	Male	DBH	30	63.03	48.14	16.79	141.17	0.457	0.224
		H	30	22.42	23.64	7.73	8.90	0.654	0.309
		AGB	30	2219.31	2168.66	3.35	5766.20	0.556	0.264

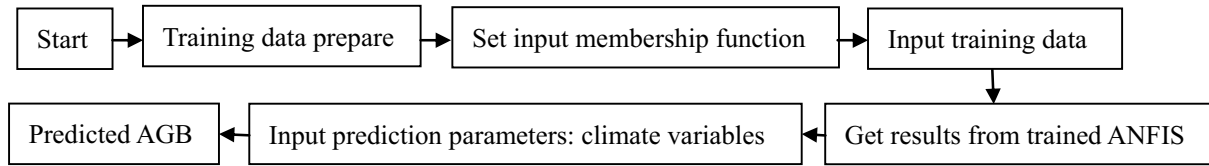


Fig. 3. The calculation steps of ANFIS model. ANFIS refer to adaptive neuro-fuzzy inference systems.

topology is made up of the key internal parameters and algorithms that ultimately determine the range of errors required to achieve the desired efficiency through trial and error. We use the mean square error (MSE) to calculate the network errors (Dou and Yang, 2017):

$$MSE = \frac{1}{N} \sum_{i=1}^N (o_i - t_i)^2 \quad (2)$$

where N is 300; o_i is the network output and t_i is the target. The minimum AGB error is achieved at 34 iterations.

2.3.2. Support vector machines (SVM)

The basic principle of an SVM is a quadratic algorithm which is able to find the best hyperplane, and all samples are separated from the maximum interval boundaries (Li et al., 2014). The SVM shows many unique advantages in solving small sample, nonlinear and high-dimensional pattern recognition problems. This method is used to analyze linearly separable cases. In the case of linear inseparability, the nonlinear mapping algorithm is used to transform the linearly indivisible sample of the low-dimensional input space into a high-dimensional feature space to make it linearly separable, so that the high-dimensional feature space is adopted. The linear algorithm makes it possible to perform a linear analysis of the nonlinear characteristics of the sample (Zhang et al., 2015). In this study, the value and core width of the regularization factor were determined by the grid search method. The insensitive value error bandwidth defaults as 0.01. In SVR, we used monthly climate variables (such as average minimum temperature, average maximum temperature, average temperature, average relative humidity, and precipitation) as the inputs. The actual AGB value was the output. The kernel function (linear, Gaussian, sigmoid, radial basis, and polynomial, etc.) computes the inner product of the input feature vectors in high-dimensional space and reduces the time and space complexity of the SVR method. The radial basis kernel function is used in the SVR to predict the AGB. We used the following equation to calculate the kernel function, which is defined as nonlinear mapping from the input space to a high-dimensional feature space:

$$f(x) = w^T x + b = \sum_{i=1}^m a_i y_i x_i^T x + b \quad (3)$$

in which, for the training data $\{(x_1, y_1), \dots, (x_n, y_n)\}$, the SVR utilizes the input vector x , which is the monthly climate variables, and calculates the function that best describes the actual output, where w is the slope of the separating hyperplane, and b is a bias factor. We determined the model parameters before the model selection. The kernel function uses similar parameter values, cost = 1, $\gamma = 0.52$ and $\xi = 0.2$ for the SVR models to predict the AGB. However, the number of support

vectors varies approximately 39 for the SVR models.

2.3.3. Generalized regression neural network (GRNN)

Compared with the traditional ANN method, GRNN has a strong nonlinear mapping ability and learning speed and requires fewer samples. Another advantage is that GRNN does not require a great deal of effort to determine its inherent functions or parameters unless it is a smoothing factor that significantly affects the generalization ability of the model. Currently, no universally accepted methods are able to obtain the best smoothing factor to ensure the accuracy of the GRNN model. In the current study, an iterative process using quad cross-validation is utilized to determine the optimal smoothing factor according to our experience and other applied research results, and this factor ranges from 0.01 to 1 (Dou and Yang, 2017). The probability density function used in GRNN is the normal distribution. The function is:

$$AGB = \frac{\sum AGB_i k(x, x_k)}{\sum k(x, x_k)} \quad (4)$$

where x is the input that is the average minimum temperature, average maximum temperature, average temperature, average relative humidity and precipitation, AGB_i is the activation weight for the pattern layer neuron at k , $k(x, x_k) = e^{-d_k/2\sigma^2}$, $d_k = (x - x_k)(x - x_k)^T$, where d_k is the squared Euclidean distance between the training samples x_k and the input x . The steps for the calculations in this study include 1) calculating distances $d_1, d_2, \dots, d_k$ (1.26, 0.97, 1.53, 0.68, 1.05); 2) calculating weights using the activation function $e^{-d_k/2\sigma^2}$; 3) summing w 's, $W = w_1 + \dots + w_k$ and the numerator was $AGB^*w = w_1^*AGB_1 + \dots + w_k^*AGB_k$; and 4) calculating the predicted output AGB^*w/W .

2.3.4. Adaptive neuro-fuzzy inference system (ANFIS)

Advanced ANFIS technology can qualitatively and quantitatively characterize the nonlinear processes that determine the influence of climate factors on forest biomass, as shown later in this study. It is especially noteworthy that the efficiency and potential of ANFIS depend on the method used to generate the FIS. Meshing, clustering and fuzzy c-means clustering methods were used to generate the fuzzy inference systems. ANFIS models based on Takagi and Sugeno (1985) were developed in this study (Dou and Yang, 2017). The calculation steps are as follows (Fig. 3): (1) compare the input variables with the membership functions on the premise part to obtain the membership values of each linguistic label; (2) combine the membership values on the premise part to obtain the firing strength (weight) of each rule; (3) generate the qualified consequent of each rule depending on the firing strength; and (4) aggregate the qualified consequents to produce a crisp output (Fig. S4). In this study, the input vector x was the average minimum

Table 3
Parameter information of the adaptive neuro-fuzzy inference systems (ANFIS) model.

Parameters					Gradient descend algorithm	
Number of layers	Size of input dataset	Number of output	Membership functions	Learning rules	Momentum constant	Number of epoch
4	260	1	Gauss	Least squares estimation	0.8	100

temperature, average maximum temperature, average temperature, average relative humidity, or precipitation, while AGB was the output. The probability is analyzed during the data selection process. The potential outliers were eliminated. After this process, 260 climate data and AGB observations were selected for analysis in this study (Table 3). In the model construction process, the ANFIS model parameters are determined to be minimal in the learning phase of the specific era. The test dataset was used to verify the accuracy and effectiveness of the training model.

2.3.5. Group method of data handling (GMDH)

The GMDH can be used to model systems without system-specific knowledge. The network topology of this inductive learning method can be flexibly developed by a self-organizing heuristic algorithm. In the GMDH network, all hidden nodes that served as activation functions are connected to a single output via one or two inputs. Each node can use a quadratic two-variable polynomial regression, which indicates that the equation has five weights and one deviation. After achieving the best complex network, a higher order can generate iterative polynomial series related to all nodes used in the network (Sheikholeslami et al., 2014).

For each pair of input variables, we would find a set of coefficients of the regression. As we have m input variables, we would have $m(m-1)/2$ different combinations of input variables. There is an associated AGB output of the training set that best fits the dependent AGB observations in the training set. We computed 10 regression polynomials from the observations. We evaluated the polynomial at every n data points to calculate a new estimate Z . We interpreted these new variables as new, improved variables to have better predictability properties. Comparing each column of Z with the dependent variable Y , a new Z would replace the original input data. We propagated the predicted value successively to higher layers of the algorithm. When the mean-squared error between the predicted and the measured values of the given output variable was less than a desired value, the iteration was stopped. A connection between inputs and outputs can be expressed by the series functions of Volterra:

$$AGB = a + bx_1 + cx_2 + dx_3 + ex_4 + fx_5 \quad (5)$$

where $x_1, \dots, x_5$ are the climate variables. The following procedure is used for a given set of 300 observations of the 5 climate variables and their associated matrix $\{AGB_1, AGB_{300}\}$.

2.4. Data for model training and validation

The input variables for all models are climate variables and DBH, H, and crown width. The five different ML modeling techniques presented in the previous section have been developed and compared. To achieve accurate and reasonable comparisons of different AGB estimates, according to the strong correlation between climate variables and each AGB, as shown in Table 2, all AGB values of female and male trees were modeled using the same input variables (average minimum temperature, average maximum temperature, average temperature, average relative humidity, precipitation) and prediction methods. These input variables and corresponding output variables are normalized to a range between 0 and 1 before training each application model. The toolboxes in the MATLAB software (version 8.2, The MathWorks, Inc., Natick, MA, USA), including the Neural Network Toolbox 8.1 (<http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.699.4831&rep=rep1&type=pdf>) and the Fuzzy Logic Toolbox 2.2.18 (https://www.researchgate.net/profile/Ecir_Ugur_Kucuksille/publication/262008080), were utilized for all models (Li et al., 2014). The SVM model can be downloaded from <https://www.csie.ntu.edu.tw/~cjlin/libsvm/>.

2.5. Model evaluation

The data processing performance of the developed model was evaluated on the basis of several statistical data indices, including the coefficient of determination (R^2), Nash-Sutcliffe efficiency (E_{NS}), root mean squared error (RMSE), and mean absolute error (MAE) (Fu et al., 2017). The above statistical indicators are described as follows:

$$R^2 = \left[\frac{\sum_{i=1}^N (Y_{a,c} - \bar{Y}_a)(Y_{b,c} - \bar{Y}_b)}{\sqrt{\sum_{i=1}^N (Y_{a,c} - \bar{Y}_a)^2 \sum_{i=1}^N (Y_{b,c} - \bar{Y}_b)^2}} \right]^2 \quad (6)$$

$$RMSE = \sqrt{\sum_{i=1}^N (Y_{a,c} - Y_{b,c})^2 / N} \quad (7)$$

$$E_{NS} = 1 - \sum_{i=1}^N (Y_{a,c} - Y_{b,c})^2 / \sum_{i=1}^N (Y_{a,c} - \bar{Y}_b)^2 \quad (8)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |Y_{a,c} - Y_{b,c}| \quad (9)$$

where Y_a and Y_b denote the observed and modeled values, respectively; $\bar{Y}_a$ and $\bar{Y}_b$ are the means of the observed and modeled values, respectively; and N is the number of observed values.

2.6. Estimating future biomass

The models mentioned above were applied to predict the future AGB of *D. pierrei* with the same dataset (Table 2) at each sampled site under future climate scenarios in China. The relative difference in AGB between the current and future climate scenarios (R_{AGB}) is derived used Equation (10):

$$R_{AGB} = \frac{AGB_{f/DBH} - AGB_{c/DBH}}{AGB_{c/DBH}} \times 100\% \quad (10)$$

where R_{AGB} is the relative difference in AGB between current and future climate scenarios, and $AGB_{c/DBH}$ and $AGB_{f/DBH}$ are the measured and estimated AGB values at the same DBH under the current and future scenarios, respectively.

To avoid future uncertainties in DBH predictions and to ensure reasonable comparisons, sample trees with measured values are considered to be invariant applications in estimating the future AGB of *D. pierrei* under future climate scenarios (Beaumont et al., 2008). Therefore, the impact of climate on the changes in AGB in the future scenarios was evaluated under constraint conditions. We used the latest climate change scenarios from the IPCC Fifth Assessment Report based on the reduced global climate model (GCM) applied in three representative concentration paths (RCPs): RCP 2.6, RCP 4.5, and RCP 8.5 (Ipcc, 2013; Moss et al., 2010). These scenarios show low, medium, and high concentrations of greenhouse gases and predicted radiative forcing. The GCM is a Beijing Climate Center Climate System Model developed for China (BCC-CSM1-1). The future climate data for 2041–2060 and 2061–2080 with a spatial resolution of $1 \text{ km} \times 1 \text{ km}$ were downloaded from the WorldClim dataset (Fu et al., 2017).

3. Results

3.1. Modeling aboveground biomass of female trees

Larger R^2 and E_{NS} values and smaller RMSE and MAE values indicate higher model efficiency (Table 4). The model calculation results during training indicated that ANFIS had the largest R^2 , E_{NS} , RMSE and MAE values, followed by GRNN, and GMDH had the smallest values. The validation and testing processes indicated that GRNN had the largest R^2 , E_{NS} , RMSE and MAE values, followed by SVM, and GMDH had the smallest values.

Table 4

Comparisons of models for female and male aboveground biomass (AGB) for the training, validation, and testing periods.

Gender	Model	Training				Validation				Testing			
		R ²	E _{NS}	RMSE	MAE	R ²	E _{NS}	RMSE	MAE	R ²	E _{NS}	RMSE	MAE
Female	GMDH	0.9126	0.8105	0.9521	0.6464	0.8340	0.6773	0.9703	0.9289	0.8284	0.6823	0.9026	0.8307
	GRNN	0.9499	0.8990	0.6107	0.3861	0.8961	0.7871	0.7296	0.4527	0.9006	0.8049	0.6533	0.4078
	ANFIS	0.9558	0.9035	0.5265	0.3437	0.8684	0.7758	0.8867	0.8758	0.8736	0.7908	0.7834	0.7300
	SVM	0.9373	0.8987	0.7946	0.4758	0.8960	0.7863	0.8779	0.6020	0.8978	0.7963	0.7519	0.5232
	ANN	0.9212	0.8885	0.8762	0.6389	0.8948	0.7842	0.8825	0.8056	0.8970	0.7943	0.7757	0.7009
Male	GMDH	0.8779	0.7300	0.9283	0.6378	0.8408	0.6680	0.9022	0.9295	0.8231	0.6428	0.8994	0.7766
	GRNN	0.9195	0.8138	0.5133	0.3351	0.8833	0.7419	0.8240	0.8763	0.8407	0.7521	0.7807	0.6948
	ANFIS	0.9138	0.8097	0.5954	0.3775	0.9160	0.7482	0.8200	0.8061	0.8498	0.7556	0.7730	0.6711
	SVM	0.8862	0.8003	0.8543	0.6303	0.9175	0.7497	0.8157	0.6024	0.8501	0.7577	0.7493	0.5268
	ANN	0.9017	0.8095	0.7747	0.4672	0.9176	0.7503	0.6769	0.4530	0.8512	0.7663	0.6510	0.4331

Note: GMDH refer to group method of data handling; GRNN refer to generalized regression neural networks; ANFIS refer to adaptive neuro-fuzzy inference systems; SVM refer to a support vector machine; ANN refer to an artificial neural network; R² is the coefficient of determination; E_{NS} is the Nash-Sutcliffe efficiency; RMSE is the root mean squared error; MAE is the mean absolute error.

The fitted lines of the GRNN model (slope = 0.946) and SVM model (slope = 0.940) were close to the ideal line (1:1 line). The fitted line (slope = 0.870) of the GMDH model was more inconsistent with the ideal fit line than those of the ANN (slope = 0.927) and ANFIS

(slope = 0.911) models (Fig. 4). In addition, none of the values estimated by the GMDH matched the minimum values around the corresponding observations. Although the applied models exhibited significant differences in AGB prediction performance (Table 4), these

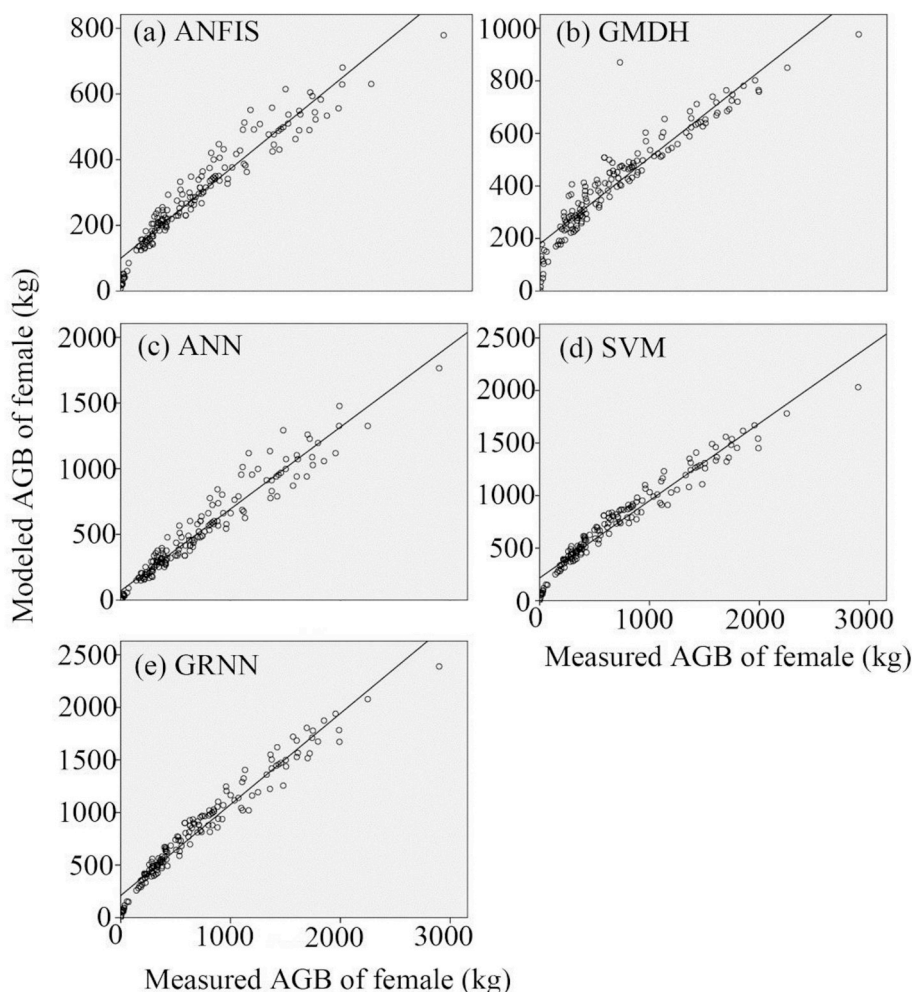


Fig. 4. The female aboveground biomass measured and predicted by models for the testing period. (a) ANFIS model; (b) GMDH model; (c) ANN model; (d) SVM model; and (e) GRNN model. AGB is aboveground biomass of female of *Dacrydium pierrei*; ANFIS refer to adaptive neuro-fuzzy inference systems; GMDH refer to group method of data handling; ANN refer to artificial neural network; SVM refer to support vector machine; GRNN refer to generalized regression neural networks.

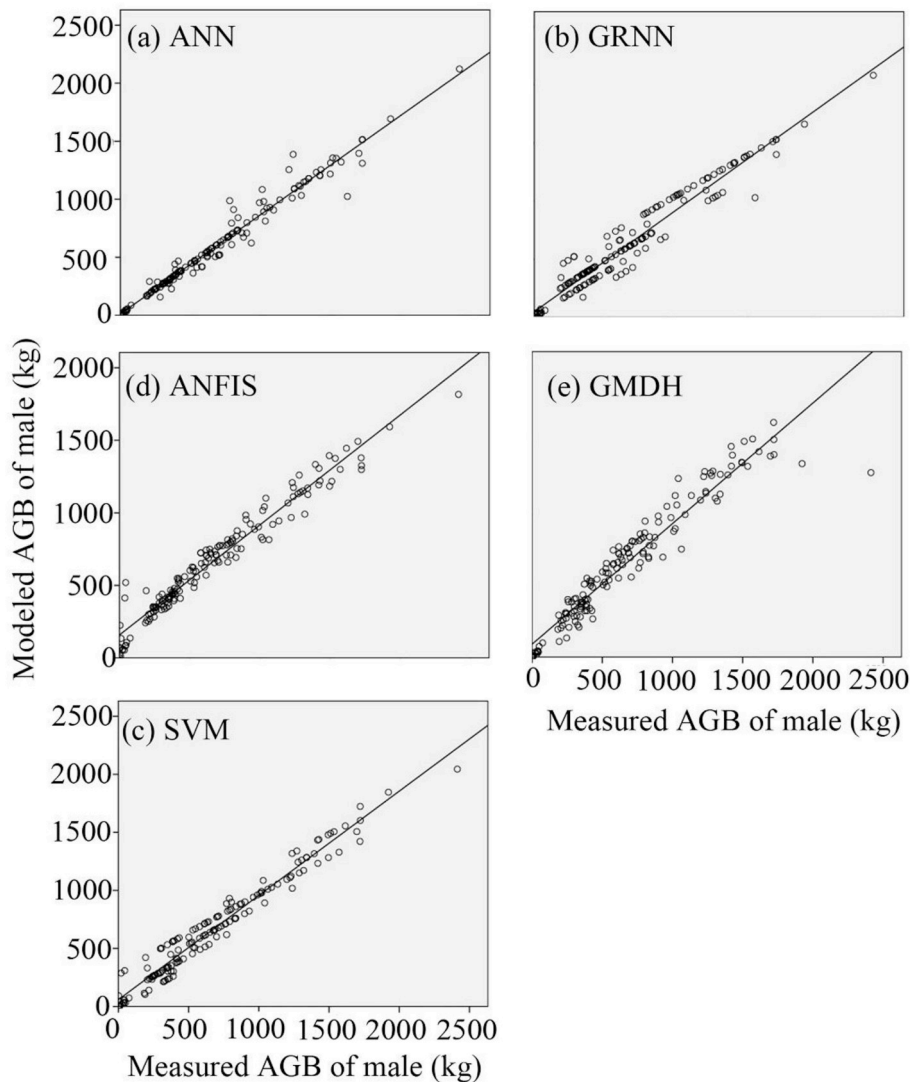


Fig. 5. The male aboveground biomass measured and predicted by models for the testing period. (a) ANN model; (b) GRNN model; (c) SVM model; (d) ANFIS model; and (e) GMDH model. AGB is aboveground biomass of male of *Dacrydium pierrei*; ANN refer to artificial neural network; GRNN refer to generalized regression neural networks; SVM refer to support vector machine; ANFIS refer to adaptive neuro-fuzzy inference systems; GMDH refer to group method of data handling.

models provided similar overall dispersion estimates (Fig. 4). Therefore, we described only the monthly and annual changes in AGB in female trees estimated by GRNN.

3.2. Modeling aboveground biomass in male trees

The GMDH model that estimated the AGB of male trees also resulted in the lowest model efficiency during testing, while the ANN model provided the best performance based on the R^2 , E_{NS} , RMSE and MAE indicators during validation and testing (Table 4). The SVM together with the ANN exhibited better performance than the GMDH and ANFIS models during validation and testing. The GRNN model exhibited better performance than the ANFIS, ANN, and SVM models during training.

The fit lines of the ANN model (slope = 0.951) (1:1 line), SVM model (slope = 0.940), ANFIS model (slope = 0.934), and GRNN model (slope = 0.926) were close to the ideal fit line, while the fit line of the GMDH model (slope = 0.902) was more inconsistent with the ideal fit line than those of the other models (Fig. 5). In addition, none of the values estimated by the GMDH model matched the minimum value around the corresponding observations. Although the applied models had significant differences in male AGB prediction performance (Table 4), these models provided similar overall

Table 5
Model performance rankings of the models for aboveground biomass (AGB) for the testing period.

Model	ANN	GRNN	SVM	ANFIS	GMDH
AGB _{female}	3	1	2	4	5
AGB _{male}	1	4	2	3	5

Note: Model performance rankings were determined according to the R^2 , NSE, RMSE and MAE indices. R^2 is the coefficient of determination; E_{NS} is the Nash-Sutcliffe efficiency; RMSE is the root mean squared error; MAE is the mean absolute error. AGB_{female} is aboveground biomass of female *Dacrydium pierrei*; AGB_{male} is aboveground biomass of male *Dacrydium pierrei*; ANN refers to an artificial neural network; GRNN refer to generalized regression neural networks; SVM refer to the support vector machine; ANFIS refer to adaptive neuro-fuzzy inference systems; GMDH refer to the group method of data handling.

dispersion estimates (Fig. 5).

The model performances of AGB_{female} predictions could be ranked as follows: GRNN, SVM, ANN, ANFIS and GMDH, and those of AGB_{male} were ANN, SVM, ANFIS, GRNN and GMDH (Table 5).

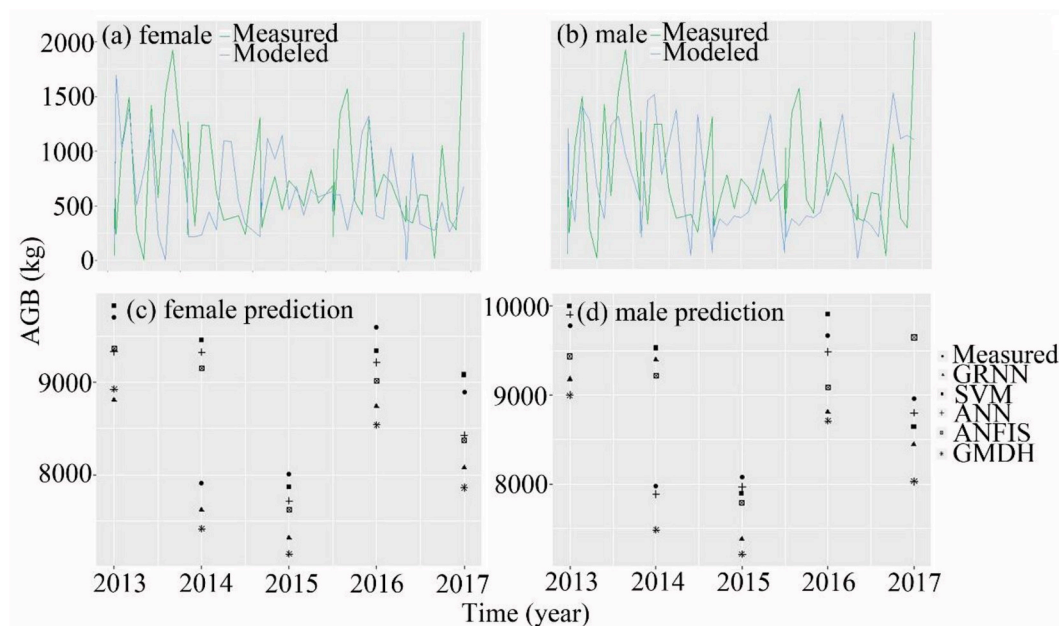


Fig. 6. Measured and modeled the aboveground biomass of *Dacrydium pierrei* by models in the whole period from 2013 to 2017. AGB is aboveground biomass of *Dacrydium pierrei*; (a) female refer to the AGB of measured and modeled is female *Dacrydium pierrei*; (b) male refer to the AGB of measured and modeled is male *Dacrydium pierrei*; (c) female prediction refer to the AGB predicted by ANFIS, GRNN, SVM, ANN and GMDH model comparing with the measured AGB; (d) male prediction refer to the AGB predicted by GRNN, SVM, ANN, ANFIS and GMDH; ANN refer to artificial neural network; GRNN refer to generalized regression neural networks; SVM refer to support vector machine; ANFIS refer to adaptive neuro-fuzzy inference systems; GMDH refer to group method of data handling.

3.3. Biomass simulation for 2013–2017

The simulations by the GRNN and ANN models had similar results (Fig. 6). However, these models exhibited overestimated or underestimated phenomena during certain periods. The peak AGB values were overestimated in 2014 and 2016, especially during verification and testing (Fig. 6a and b). However, the overestimations and underestimations of AGB_{female} were stronger than those of AGB_{male} (Fig. 6a and b). In addition, the model predictions in both 2015 and 2016 underestimated the AGB in comparison to actual measurements (Fig. 6c). All models underestimated the AGB, except for the GRNN model in 2017 (Fig. 6c), and only the SVM model overestimated the AGB in 2016 (Fig. 6d). All models underestimated the AGB, except the ANFIS model in 2017.

3.4. AGB estimates under future climate scenarios

The results showed that the AGB exhibited both increasing and decreasing trends (Fig. 7). The predicted AGB increased with the increase in regional climate factors. The variation in AGB was not large in different locations during the same time period under the three climate scenarios. The estimated AGB of females in WZS was slightly higher than that in the other three sites (Fig. 7a and b). The greatest increase ($30.0 \pm 33.6\%$ (mean $\pm$ standard deviation)) in AGB was predicted in WZS for the period 2061–2080 under the RCP 8.5 climate scenario. The estimated average AGB of males was highest for RCP 8.5, followed by RCP 4.5; the lowest was in RCP 2.6, and the average from 2061 to 2080 was higher than that from 2041 to 2060 (Fig. 7c and d). The AGB of females was predicted to increase from the current levels under the RCP 2.6, RCP 4.5, and RCP 8.5 climate scenarios by $13.0 \pm 31.4\%$, $16.6 \pm 30.7\%$, and $18.5 \pm 30.9\%$ during the period from 2041 to 2060 (Fig. 7a) and $15.6 \pm 32.1\%$, $21.2 \pm 33.2\%$ and $24.8 \pm 32.7\%$ from 2061 to 2080, respectively (Fig. 6b); the AGB of males was predicted to increase by $16.3 \pm 32.3\%$, $21.7 \pm 32.5\%$ and $22.9 \pm 32.6\%$ during 2041–2060 (Fig. 7c) and by $22.3 \pm 30.8\%$, $27.2 \pm 31.8\%$ and $30.1 \pm 34.4\%$ during 2061–2080 (Fig. 7d).

4. Discussion

Climate change affects forest carbon storage, tree growth and AGB accumulation (Stegen et al., 2011). Climate variables need to be considered when exploring the cumulative effects of climate change on tree biomass. In this study, we investigated the adaptability and effectiveness of various machine learning technologies, including ANN, SVM, GRNN, ANFIS, and GMDH. We established and predicted the AGB of *D. pierrei* using field measurement data. The efficiencies of the models were reflected by R^2 , E_{NS} , RMSE, and MAE. The results showed that the impacts of climate change on AGB were quantitatively described by the simulations and predictions with machine learning techniques.

4.1. Characteristics of AGB changes

The result showed environmental forcing variables caused the seasonal and interannual fluctuations in AGB (Fig. 6). The reasons for this phenomenon were that *D. pierrei* has unique phenological characteristics; specifically, its flowering period is from April to March, and then the buds fell off with some immature seeds, and its seed maturation period occurs from October to November or December, so the AGB changes during this period are different from those in different months. The AGB in 2014 was less than that in 2013 and 2015, resulting in annual changes. It is worth noting that most of the AGB models during the peak of the growing season and the annual period significantly underestimated the AGB during validation and testing. Because of the physiological structuring characteristics of seasonal reproduction, the changes in forest biomass are seasonal (Soudijn and de Roos, 2017). The model fitting showed that these nonstationary features in environmental variables may cause potential problems that hinder forest productivity.

In addition, the AGB of males was slightly larger than that of females. Dioecious plants usually have gender-related life history features. Males typically reach sexual maturity earlier than females (Trivers, 1976), exhibiting faster vegetative growth rates and lower mortality, which makes males more resistant to both biological and

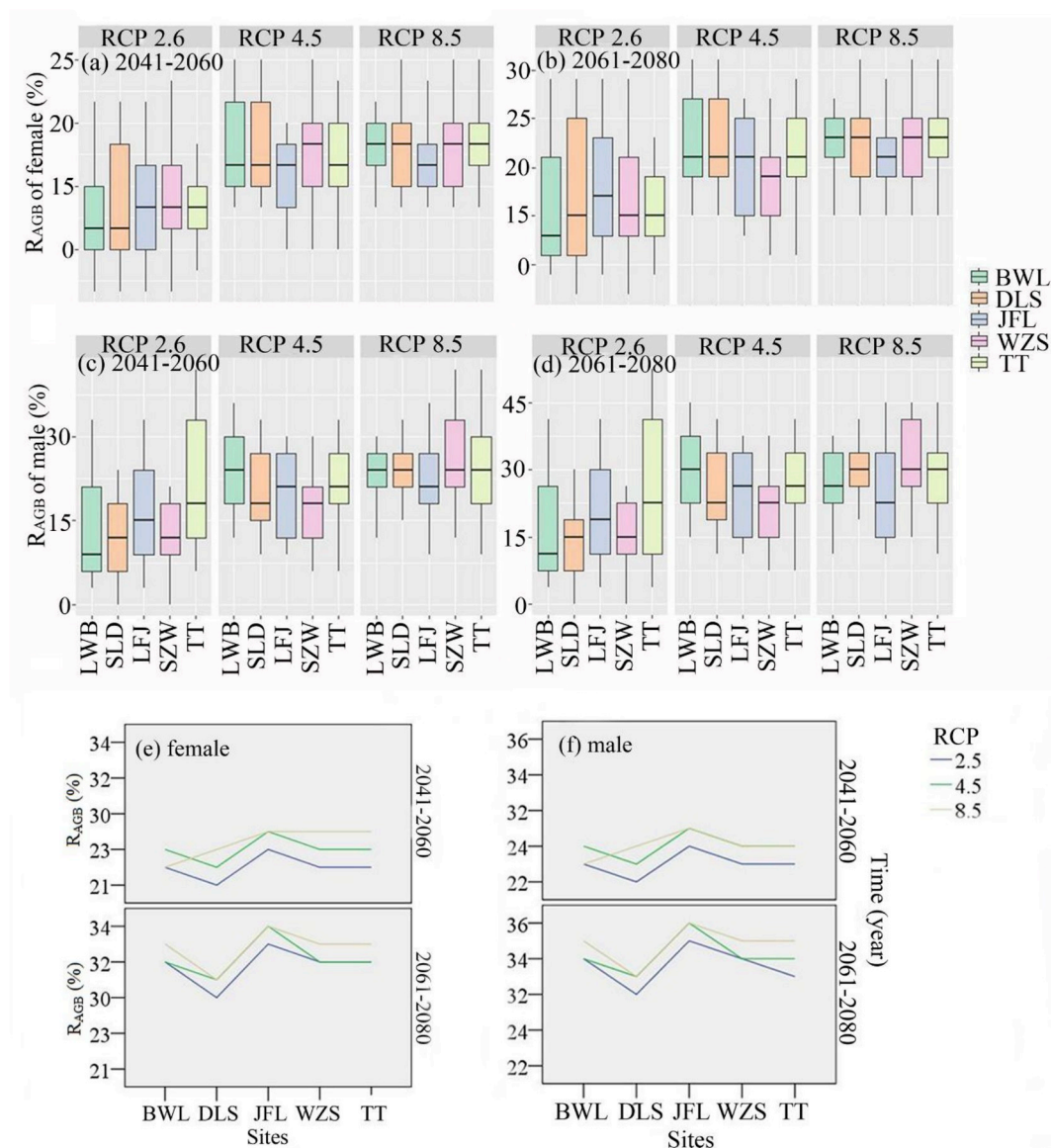


Fig. 7. The relative difference in predicted aboveground biomass of *Dacrydium pierrei* between current and future climate scenarios: RCP 2.6, RCP 4.5 and RCP 8.5 during the period of 2041–2060 and 2061–2080 for the four distribution sites and the total distribution areas of *Dacrydium pierrei* in China. Note: R_{AGB} refer to the relative difference in AGB between current and future climate scenarios (Equation (5)); RCPs refer to representative concentration paths; (a)–(d) the box plots of R_{AGB} and (e)–(f) the distributions of the mean values of R_{AGB} for the female and male of the sampling trees; (a) R_{AGB} of the female of sampling trees in the 2041–2060 year period (RCP 2.6, RCP 4.5, RCP 8.5); (b) R_{AGB} of the female of sampling trees in the 2061–2080 year period (RCP 2.6, RCP 4.5, RCP 8.5); (c) R_{AGB} of the male of sampling trees in the 2041–2060 year period (RCP 2.6, RCP 4.5, RCP 8.5); (d) R_{AGB} of the male of sampling trees in the 2061–2080 year period (RCP 2.6, RCP 4.5, RCP 8.5); BWL, JFL, DLS, WZS and TT represent the Bawangling National Nature Reserve, the Jianfengling National Forest Park, the Diaoluoshan National Forest Park, the Wuzhishan National Nature Reserve and total research sites in China.

abiotic impacts (Cipollini and Whigham, 1994; Pan et al., 2010). Female trees need to use some of their own biological energy to form buds, flower, and produce fruits. Therefore, female trees exhibit slightly lower AGB accumulation than male trees.

4.2. Impacts of climate change on AGB

The results showed that the variables related to temperature, humidity, and precipitation are of great significance in explaining the changes in AGB. Increasing temperatures and new patterns of precipitation due to climate change result in changes in the morphology, physiology, growth, reproduction, and biology of trees, all of which affect AGB (Stegen et al., 2011). In addition, enhancing the use efficiency of water and light resources could increase forest productivity (van der Sande et al., 2017). Additionally, water deficiency has the

most severe effect on the process of biomass formation (van der Sande et al., 2017). Climate change is leading to increasing global temperatures and droughts in many areas, which have changed the nutrients in vegetation, AGB and belowground biomass (Peñuelas et al., 2016). Rainfall is highly correlated with the increase in tree stem diameter, which affects the accumulation of AGB, while rainfall together with temperature affects the AGB (Ogaya and Peñuelas, 2007). Tropical mountain forests may contain higher amounts of AGB than before to ensure that they will remain enhanced in the ever-changing climate in the future (Venter et al., 2017). In addition, the increase in precipitation that results in a decrease in AGB can also be explained by the biological properties of *D. pierrei* (Turner and Cernusak, 2011).

The results showed that the region of *D. pierrei* distribution had a specific climate, which is similar to the results found in previous studies (Wyse et al., 2016). The environment for the growth of *D. pierrei* is a

tropical mountain rainforest with slightly lower temperatures, but the inter annual temperature changes are small; the annual rainfall is rich and evenly distributed because of the relatively high relative humidity from clouds and fog, and the altitude is above 1000 m (Turner and Cernusak, 2011). In the tropical mountain rainforest region, although there is sufficient precipitation (average annual precipitation is 1000–1800 mm), the high temperature throughout the year has the potential to increase the growth of trees, which is suitable for the growth of *D. pierrei* (Norton et al., 1988).

4.3. Advantages and uncertainties of the model

The monthly values in the AGB were explained by the model, which showed that the average values for male and female *D. pierrei* were 95% and 90%, respectively (Table 4). Therefore, these ML techniques are capable of describing the relationships between climate change and environmental factors and the AGB. These results are similar to previous studies that found that ML-based data processing techniques are effective at modeling and predicting forest biomass (Akkaya, 2016; Foody and Cutler, 2006; Vahedi, 2016; Were et al., 2015). The best model was the ANN, which predicted the AGB with higher accuracy than the allometric equation. The ANFIS-based model is an effective technique for obtaining high-precision predictions of biomass with high heating value (Akkaya, 2016). Furthermore, ANN and ANFIS can be used to establish a dynamic behavioral model (Ramzi et al., 2015). Additionally, the models we proposed have achieved higher accuracy in testing compared with the above results. In summary, our current proposed models have great potential for estimating AGB. These models can be considered alternative tools for the traditional AGB models across regional or global scales for different vegetation types.

According to the performance of the various AGB models in this study, no one model consistently outperformed the others for all AGB estimates. The GMDH model consistently produced relatively worse simulation results compared with the other models. This result may be partly due to the inherent limitations of the GMDH model, such as the choice of input parameters, multicollinearity and overfitting (Villaverde and Barreiro, 2016). In addition, the effects of random errors in AGB observations on different time scales (e.g., daily, monthly, and yearly) should be taken into consideration when assessing the differences in predictions (Lindner et al., 2010; Vahedi, 2016). Systematic errors can also increase the uncertainty of the AGB estimates. Moreover, AGB is strongly influenced by the complex interactions between photosynthesis and photosynthetic efficiency (Huntingford et al., 2008). The selection of effective driving variables as model inputs could be used to further improve the predictive power of the model, especially for the AGB, and this is of significant importance for future work.

4.4. Management perspectives

The models used in this study to predict the impact of future climate change on AGB are ideal, and the results indicated that the DBH growth of the sampled trees is related to climate change (Girard et al., 2014). However, in addition to temperature, humidity, rainfall and climate-related variables, other factors such as tree height, crown width, development stage, forest type, stand density, and interspecies competition may contribute significantly to the DBH changes of a tree (Iizuka et al., 2018). Some of these factors interacted and differed from each other. Future climate change will lead to increased complexity of future AGB estimates. There are very large uncertainties related to this method when the DBH growth of sampled trees is considered.

The AGB showed both decreasing and increasing trends during the periods of 2041–2060 and 2061–2080 in the future climate scenarios. The reason for this difference is that future climate change will make the survival of *D. pierrei* more difficult, and the distribution of this species will decrease in China and globally. Climate changes lead to changes in the growth environment of the *D. pierrei* community, which

also results in biomass changes. According to the results mentioned above, we should take appropriate measures to improve the climate conditions, prevent the climate from deteriorating in the future, make the environment more adaptable to the growth of *D. pierrei*, and prevent species from becoming rare and endangered. Extreme climate events will bring more serious harm to the living environments for rare and endangered species. We should take appropriate management measures, such as thinning trees, artificial tending measures and so on, during the summer to reduce water consumption that is needed for tree growth. In addition, the actual niche will also change with the changes in the competition and the composition of different species with climate change, and the succession and development of ecosystems are the result of this mutual competition between different species. We should consider the role of intermediate competition in the prediction of future climate change simulations. In future climate scenarios, artificial management measures should be used to reduce the plants growing around *D. pierrei* and expand the future distribution range of *D. pierrei* and other rare and endangered tree species. The forest ecosystems, productivity, species composition and structure of forests, and the biogeochemical cycle of forests would all be affected by global climate change. We should reduce man-made pollution to ensure the survival of the environment, reduce the emissions of polluting gases, slow the pace of climate deterioration, improve the environmental conditions of tree growth, and expand the distribution of rare and endangered tree species, increasing the number of species to ensure the growth and the productivity of the forest.

According to ML models in this study, we estimated that the AGB of *D. pierrei* would increase by 13.0%–31.8% during 2041–2080 under future climate change (Fig. 7). Therefore, the absence of climate variables in traditional biomass equations will produce some bias in biomass estimates. Predicting the impact of climate change on AGB requires consideration of climate uncertainties and climate scenarios. Our research also clearly showed the positive impact of future climate change on the AGB of *D. pierrei*. Uncertainty needs to be further addressed when potential factors affecting tree biomass are investigated in the future.

5. Conclusions

In this modeling study, we have made several attempts to determine the optimal internal structures, functions and parameters of models. We developed and identified a reliable ML modeling (GRNN and ANN) approach to predict the AGB of *D. pierrei* in China. We also estimated the AGB of *D. pierrei* in China by using the ML models with the best performance, which indicated that the AGB would increase during 2041–2080 under the RCP 2.6, RCP 4.5 and RCP 8.5 climate scenarios. Therefore, climate variables should be added to the biomass model equations used to estimate biomass. To obtain more useful and reliable biomass information, it is crucial to apply ML models in further follow-up studies. In addition, optimal artificial management measures should be used to reduce the pressure of interspecific competition on *D. pierrei* and to improve the moisture and temperature conditions in order to improve the growth of *D. pierrei*.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jenvman.2018.12.090>.

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